

A Comprehensive Review of Edge-AI Frameworks for Predictive Fault Analysis in Smart Microgrids

Mrs. Renjini E Nambiar¹, Mrs. Gayathri R², Mr. Kirit M Hothi³, Mr. P. Balaji⁴, Mr. Minnakanti Ajay Babu⁵

^{1,2}Assistant Professor, Department of Electrical and Electronics Engineering, MVJ College of Engineering, Bengaluru

³Lecturer, Department of Electrical and Electronics Engineering, A. V. Parekh Technical Institute, Rajkot

⁴Associate Professor, Department of Computer Science Engineering, Siddharth Institute of Engineering and Technology, Puttur

⁵Assistant Professor, Department of Computer Science Engineering, Sri Mittapalli College of Engineering, Tummalapalem

Abstract—The integration of Internet of Things (IoT) devices in smart microgrids has generated massive amounts of telemetry data, making real-time fault detection a critical challenge. While cloud-based Artificial Intelligence (AI) has traditionally handled this analysis, its reliance on continuous high-bandwidth communication introduces latency, security risks, and operational bottlenecks. This paper presents a comprehensive review of the recent shift toward Edge-AI architectures in smart microgrids. By surveying contemporary literature, this review examines the core hardware components, lightweight machine learning algorithms, and communication protocols currently enabling localized predictive maintenance. Furthermore, a comparative analysis of recent methodologies is provided, highlighting the trade-offs between model accuracy and computational overhead. Finally, the paper identifies open challenges, such as data privacy and hardware constraints, and outlines future research directions for autonomous energy grids.

Index Terms—Edge-AI, Smart Microgrid, Predictive Maintenance, Internet of Things (IoT), TinyML, Federated Learning.

I. INTRODUCTION

The transition from traditional, centralized power grids to decentralized smart microgrids has fundamentally improved energy efficiency and integration of renewable sources. However, this decentralization introduces complex operational dynamics. Traditional fault detection methods rely heavily on centralized control systems, which involve

transmitting massive volumes of data to a central processing unit. This approach inherently introduces communication delays and heavily limits real-time responsiveness. To overcome these delays, Artificial Intelligence (AI) coupled with Edge Computing has enabled real-time fault analysis directly at the network edge. By deploying an AI-enabled edge device that processes sensor data locally, researchers are drastically reducing latency and dependence on cloud infrastructure. This review paper synthesizes the current state-of-the-art in Edge-AI frameworks designed for microgrid fault analysis, providing researchers with a consolidated view of current technologies, algorithms, and existing gaps in the literature.

II. THE SHIFT FROM CLOUD TO EDGE COMPUTING IN POWER SYSTEMS

The primary driver for moving intelligence to the edge in power systems is the strict latency requirement of electrical fault isolation. Standard protective relays must operate within milliseconds to prevent cascading grid failures.

1. Cloud-Based AI:

Involves transmitting high-frequency sampled data to a centralized server. While capable of running deep neural networks, this architecture fails to meet the sub-100 millisecond response times required for preventing cascading outages due to communication overhead.

2. Edge-Based AI:

Data is sampled, pre-processed, and classified locally by an embedded device. For example, recent edge computing frameworks propose moving computation entirely away from the centralized cloud to near-device edge servers to enable real-time monitoring and swift heuristic decision-making. This eliminates reliance on network stability and guarantees rapid fault isolation.

III. CORE COMPONENTS OF EDGE-AI FAULT PREDICTION

Implementing Edge-AI in a microgrid requires a synergy of specific hardware and algorithmic optimizations, often referred to as "TinyML."

A. Hardware Architectures

Current literature highlights a spectrum of edge devices used for predictive maintenance:

- **Microcontroller Units (MCUs):**

Low-cost microcontrollers like the ESP32 are increasingly used alongside hardware like ZMPT101B voltage sensors and ACS712 current sensors to capture local data and perform inferences completely independent of external networks.

- **Edge Accelerators:**

Devices such as the Raspberry Pi are frequently integrated with lightweight AI modules to process

conditioned signals directly at the substation layer, effectively acting as an intelligent node.

B. Lightweight Machine Learning Algorithms

Because edge devices lack the memory and processing power of cloud GPUs, researchers predominantly utilize optimized algorithms:

- **Quantized Neural Models:**

Models deployed via frameworks like TensorFlow Lite Micro allow neural networks to run on microcontrollers (TinyML) to classify anomalies directly at the sensor level, often triggering relay actuations in under 20 milliseconds.

Federated Learning (FL):

To address data privacy, FL enables collaborative model training without exposing sensitive microgrid information to a central server. The fault detection model is updated using parameters from local edge servers rather than raw telemetry data, reducing transmission loads while protecting terminal privacy

IV. COMPARATIVE ANALYSIS OF RECENT STUDIES

The table below synthesizes key findings from recently published literature on Edge-AI integration in power systems.

Reference	Year	AI Algorithm Used	Hardware / Platform	Key Finding & Accuracy	Limitations Noted
Singh et al.	2024	AI-Driven Framework	IoT Edge Servers	Enhanced reliability and fault tolerance in smart grids at a city scale.	High complexity in real-time encryption integration.
IJCRT Study	2026	Artificial Neural Network	Raspberry Pi / ESP32	Successfully classified single line-to-ground and three-phase faults.	Performance heavily dependent on initial signal conditioning.
IJDDT Study	2026	TinyML / Quantized NN	ESP32 (TF Lite Micro)	Achieved inference latency under 20ms with zero network reliance.	Constrained to low-complexity anomaly classification tasks.

MDPI Sensors	2025	Federated Learning (FL)	Decentralized Edge Nodes	Achieved 96% accuracy in power quality disturbance classification.	False alarm rate increased to 4% compared to centralized models.
ResearchGate	2022	Collaborative FL	Terminal-Edge-Server	Reduced data transmission while preserving system terminal privacy.	Subject to communication overhead during parameter updating.

V. OPEN CHALLENGES AND FUTURE DIRECTIONS

Despite rapid advancements, the review of current literature reveals several ongoing challenges hindering widespread commercial adoption:

1. Hardware Constraints vs. Accuracy:

While TinyML models on ESP32 devices ensure low latency, their heavily quantized nature makes distinguishing between highly similar multiclass fault types substantially more difficult.

2. Security Vulnerabilities in Distributed AI:

Decentralized designs, particularly Federated Learning, introduce new risks like data poisoning attacks, where malicious clients can corrupt local model updates to degrade the accuracy of the global grid model.

3. Data Dependency and Adaptability:

Many machine learning models currently rely on static, historical datasets. Developing algorithms that can adaptively learn in real-time to varying load profiles remains an underexplored challenge.

VI. CONCLUSION

This paper reviewed the current trajectory of Edge-AI frameworks utilized for predictive fault analysis in smart microgrids. The literature demonstrates a clear consensus: migrating machine learning inference from centralized clouds to localized edge devices resolves critical issues related to latency, bandwidth, and real-time decision-making. Lightweight algorithms, particularly TinyML neural networks on embedded microcontrollers, successfully reduce fault response times to under 20 milliseconds. Concurrently, Federated Learning offers a promising avenue for

secure, collaborative grid monitoring. For Edge-AI to become the ubiquitous standard in power infrastructure, future research must address the vulnerabilities of decentralized learning and improve real-time model adaptability under stochastic grid conditions.

REFERENCES

- [1] "AI-Enabled Edge Device for Grid Fault Analysis," *International Journal of Creative Research Thoughts (IJCRT)*, 2026.
- [2] T. Singh, S. Kumar, and B. B. Gupta, "Intelligent FaultEdge: AI-Driven Fault-Tolerant Edge Framework for Smart Grid Monitoring in IoT," *IEEE International Conference*, Aug. 2024.
- [3] "TinyML-Based Edge Intelligent Controller for Real-Time Microgrid Monitoring, Fault Detection, and Stability Enhancement," *International Journal of Drug Delivery Technology (IJDDT)*, vol. 16, no. 23s, 2026.
- [4] "Robust Federated-Learning-Based Classifier for Smart Grid Power Quality Disturbances," *Sensors*, MDPI, 2025.
- [5] "A Federated Learning-Based Fault Detection Algorithm for Power Terminals," *ResearchGate*, 2022.
- [6] "Predictive Analytics for Fault Detection and Maintenance Optimization in Smart Microgrids: A Systematic Literature Review," *International Journal of Environmental Sciences*, 2025.